Fast Eigen-based Signal Combining Algorithms for Large Antenna Arrays[1]

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Abstract—A Large array of small antennas can be used to enhance signals with very low signal-to-noise ratio and can also be used to replace large apertures. In this paper, a fast combining algorithm is proposed and analyzed to maximize the combined output signal-to-noise ratio. Our approach does not assume any sequence of trained samples and is a blind combining technique, which does not require a priori knowledge of spacecraft's or the array's spatial information. Our method for computing the optimal weight is based on the generalized *Eigen* theory and the algorithms are built upon the *Power* method. Unique advantages of our proposed algorithm include (i) no formation of covariance matrices and hence less storage is required (ii) the optimal weight is obtained with significant less efforts and thus the optimal weight can be attained more quickly (iii) our proposed algorithm is capable of handling the case when the symbol signal-to-noise-ratios at the receivers are very weak. Mathematical framework for large antenna arrays using the Eigen-based signal combining techniques along with detailed performance analysis, numerical algorithms and computer simulations are presented.

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1. INTRODUCTION

An antenna array is a collection of antennas spreading out over a field in some geometrical configurations, transmitting and receiving signals. Its primary use is to enhance the detection of signals with weak signal-to-noise ratio (SNR). With a good signal processing technique, undesired signals such as receiver's internally generated noise can be suppressed and the combined output SNR can be amplified by many folds. One of the proven techniques is called *Signal Combining*, whose main idea is to find a set of optimal weight, so that the combined signal output achieves certain objectives. A number of signal combining techniques have been studied and can be found in [1] and [2]. Our particular interests include maximizing the combined output signal power and minimizing receiver's noise. It turns out that when the receiver noise are additive white Gaussian, maximizing the combined output SNR is equivalent to maximizing the combined output power [3]. The optimal weight, as will be shown in Section 3, is the dominant eigenvectors of the Eigen problem. While such optimal weight yields the largest SNR, its calculation involves forming the covariance matrix and solving an Eigen problem. As a result, for large-size arrays, the eigen-based approaches require large computing time and memory storage. Also demand for hardware performances such as signal multipliers and signal correlators becomes expensive as the number of the antennas in the array increases. To retain the potentials and merits of the eigen-based approach while alleviating the computational costs and hardware performances, we propose an iterative algorithm, which iteratively maximizes the combined output SNR. The goal of this paper is to develop a practical numerical scheme to calculate the optimal weight as fast as possible with little or no memory storage. Our proposed algorithm, which solves for the optimal weight iteratively, is derived from a well-

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known numerical algorithm for find the dominant eigenvector, called the *Power method* [4]. Best of all, our iterative approaches bypasses the requirement of forming or inverting any covariance matrices. Moreover, due to the iterative nature of our approach, optimal weight for the previous time step can be used as an initial starting point for faster convergence. That is, the first set of optimal weight may be attained with many iterations and the consecutive weight can be found with fewer iterations when the spatial geometry of the array and spacecraft remains unchanged. Evidently, this corresponds to the acquisition phase and the tracking phase during operation.

Our paper is structured as follows. In Section 2, we develop a mathematical framework for large antenna arrays using the Eigen-based signal combining techniques and derive the numerical schemes for direct Eigen method, the Power method and the proposed matrix-free method. Performance analysis for the proposed algorithm is described in Section 3. Numerical simulations are presented in Section 4. We end the paper in Section 5 with the discussion of the schemes and some conclusions.

2. EIGEN-BASED SIGNAL COMBINING FRAMEWORK

As illustrated in Figure 1, the considered array consists of a cluster of N antennas, distributed in some arbitrary patterns. The algorithms proposed in this paper are blind combining techniques and do not assume a priori knowledge of the direction or location of the spacecraft nor the geometry of the antenna array. In addition, our schemes do not require the transmission of any trained symbols. Thus the array's phase vector is not known and the combining algorithms are implemented based solely on the observables at the receivers.

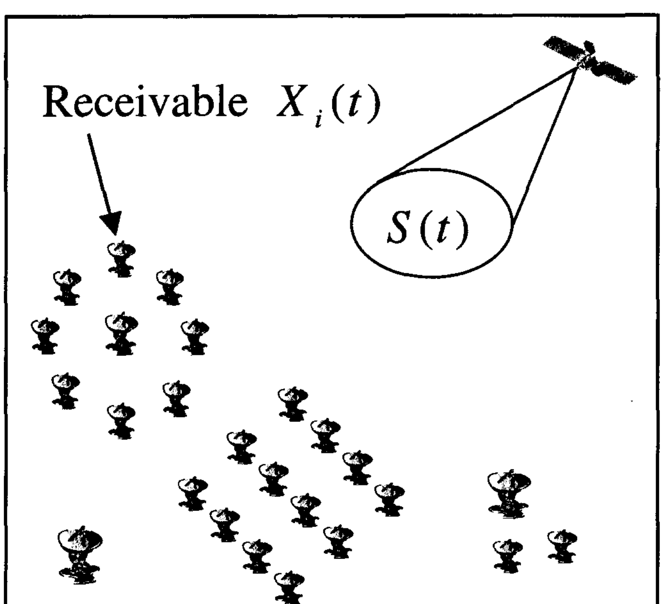

Figure 1. Large Antenna Array Geometry

The observables at receivers are denoted by $\{X_i(t)\}_{i=1}^{N}$, each of which consists of the signal from the spacecraft with some delay phase as well as the noise from the receiver. Suppose the signal to noise ratio at each receiver is sufficiently strong, then employing large antenna array techniques seems unnecessary. However if the signal to noise ratio at the receivers are very weak, large antenna array can help to amplify the signal to noise ratio. Such implementation requires the construction of a set of weight $\{w_i(t)\}_{i=1}^{N}$ so that the combined output

$$Y(t) = \sum_{i=1}^{N} \overline{w}_i X_i(t) \tag{1}$$

yields the largest possible signal to noise ratio (Figure 2). It has been shown in [3] that when the receiver's noise is of additive white Gaussian, maximizing the output's signal to noise ratio is equivalent to maximizing the output power. Thus our goal is to find an optimal set of normalized weight that maximizes the combined time-average output signal power,

$$E[\|Y\|^2] = E\left[\left\|\sum_{i=1}^{N} w_i X_i\right\|^2\right] = \vec{w}^H \Theta_{XX} \vec{w}, \tag{2}$$

where $E[\bullet]$ is the asymptotic time average expected value, the superscript H denotes the transpose conjugate operator, and Θ_{XX} is the receivable covariance matrix, whose *(i, j)*-th entry is of the form

$$\Theta_{XX}^{i,j} = E\left[X_i \overline{X}_j\right] = \frac{1}{L}\sum_{l=1}^{L} X_i(t_l)\overline{X}_j(t_l), \tag{3}$$

and L is the length of samples within a processing block.

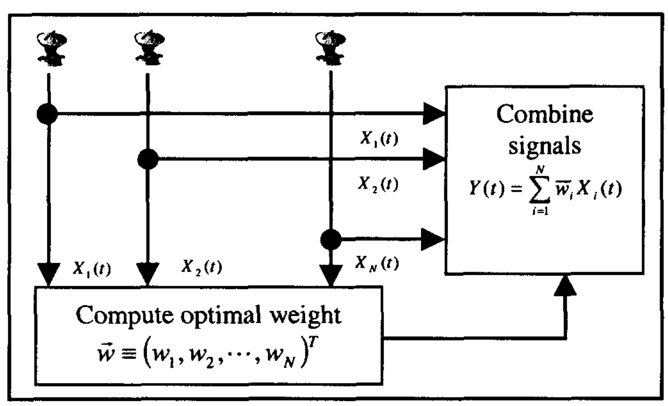

Figure 2. Signal Combining Scheme

This Eigen-based signal combining approach has been widely studied. Hackett [5] proposed this technique as a mean to adaptively separate the communication signals in an antenna array. In his study he assumed that each receivable consists of thermal noise and the signals. The thermal noise is broadband so that it can induce interferences. The optimal weight in this approach is proved to be the eigenvector corresponding to the largest eigenvalue of the covariance matrix Θ_{XX}. To demonstrate this point in a simplest manner, one can use the eigen-theory to decompose the Hermitian covariance matrix Θ_{XX} in its normal form of

$$\Theta_{XX} = V\Lambda V^H, \tag{4}$$

where

$$V = [\vec{v}_1, \ldots, \vec{v}_N], \tag{5}$$

is the matrix of normalized eigenvectors and

$$\Lambda = diag(\lambda_1, \ldots, \lambda_N), \tag{6}$$

is a diagonal matrix of eigenvalues with $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N$. It should be pointed out that the eigenvectors are complex orthonormal and $V^{-1} = V^H$. Then the optimal weight can be written as the linear combination of the eigenvectors as

$$\vec{w} = \sum_{i=1}^{N} \alpha_i \vec{v}_i = V\vec{\alpha} \text{ where } \vec{\alpha} = [\alpha_1, \ldots, \alpha_N]^T. \tag{7}$$

Consequently, the combined output power (2) becomes

$$E[\| Y \|^2] = (V\vec{\alpha})^H V\Lambda V^H (V\vec{\alpha}) = \sum_{i=1}^{N} \lambda_i |\alpha_i|^2, \tag{8}$$

It is evident from (8) that the optimal weight should be directed towards the eigenvectors in a fashion that it maximizes the combined output power. Such process along with the constraint $\|\vec{w}\| = 1$ are equivalent to finding a longest vector centered at the origin and enclosed by an N-dimensional ellipsoid whose vertices point in the direction of the eigenvectors and the semi-major axes are $\lambda_1, \lambda_2, \ldots, \lambda_N$ respectively. As a result, combined output power combined output power $E[\|Y\|^2]$ is peaked at $\lambda_{\max} = \lambda_1$ and the optimal weight is $\vec{v}_1$, the dominant eigenvector.

Direct Eigen Method

Conventional Eigen-based technique for computing optimal weight requires (a) forming the covariance matrix Θ_{XX} (order N^2L operations) and (b) solving the Eigen problem $\Theta_{XX}\vec{v} = \lambda\vec{v}$ (order N^3 operations). Both processes become expensive and impractical in term of hardware performances and speed as the size of the antenna array size (N) and the length of symbols (L) grow. Namely, its computational load is of order $(N^2L + N^3)$.

Power Method

Since the conventional technique searches for all pairs of eigenvalues and eigenvectors and uses only the dominant eigenvector, majority of its efforts in solving the Eigen problem is unnecessary. Instead, a well-known technique, called the *Power* method and can be found in any numerical analysis book, is a more appropriate choice. The aim of this technique is to determine solely the dominant eigenvector. Its implementation is simple and its approach is iterative. Starting with an initial guess $\vec{w}^{(o)}$, the subsequent iterative solutions follow

$$\vec{w}^{(k)} = \Theta_{XX}\vec{w}^{(k-1)} \text{ for } k = 1, 2, \ldots \tag{8}$$

The recursive solution $\vec{w}^{(k)}$ will converge to the dominant eigenvector $\vec{w}$ and the convergence rate depends on the ratio of the eigenvalues (λ_2/λ_1). To briefly explain the Power method, we start expressing the arbitrary initial guess $\vec{w}^{(o)}$ as a linear combination of eigenvectors of the covariance matrix Θ_{XX}

$$\vec{w}^{(o)} = a_1\vec{v}_1 + a_2\vec{v}_2 + \ldots + a_N\vec{v}_N, \tag{9}$$

with $a_1 \neq 0$. Then the recursive relation (18) implies that

$$\vec{w}^{(k)} = \lambda_1^k [a_1\vec{v}_1 + a_2(\lambda_2/\lambda_1)^k \vec{v}_2 + \ldots + a_N(\lambda_N/\lambda_1)^k \vec{v}_N]. \tag{10}$$

Since λ_1 is the dominant eigenvalue, $(\lambda_i/\lambda_1) < 1$ for $i = 2, 3, \ldots, N$, the terms $(\lambda_i/\lambda_1)^k$ converge to 0 for sufficiently large k. As a result, $\vec{w}^{(k)}$ converges to the dominant eigenvector $\vec{v}_1$ as $\Theta_{XX}\vec{w}^{(k)} = \lambda_1\vec{w}^{(k)}$. In practice, to prevent it from becoming unbounded, $\vec{w}^{(k)}$ is normalized at each iteration, i.e. $\vec{w}^{(k)} = \Theta_{XX}\vec{w}^{(k-1)} / \|\Theta_{XX}\vec{w}^{(k-1)}\|$, (see Fig. 3 for details).

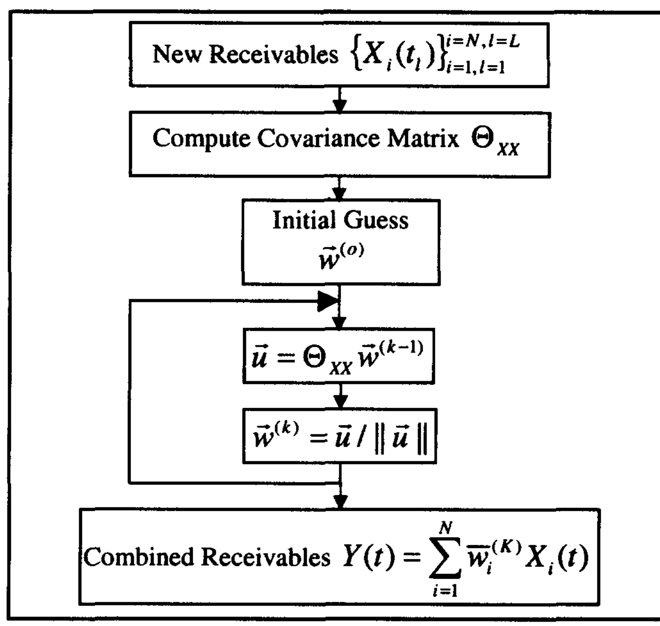

Fig. 3-Power method algorithm for dominant eigenvector

Because the *Power* method searches only for the dominant eigenvector, which is exactly what we need, it reduces only the computational costs for solving the eigen problem. Namely, one still has to form the covariance matrix (order N^2L operations) and (ii) each iteration requires a matrix-vector multiplication (order N^2 operations). The resulting computational cost is of order $N^2L + N^2K$, where K is the number of required iterations. Such computational saving is substantial if the array size N is much greater than number of symbols within a processing block L. This is hardly the case as L is significantly greater than N.

Proposed Matrix-free Signal Combining Algorithm

To reduce further the number of operations in the Power method for the maximizing the combined output power, we propose a matrix-free algorithm that bases on the Power method. Our algorithm bypasses the requirement of forming the covariance matrix, an significant advantage in speed, computational intensity and memory storage. We will demonstrate that each iterative process is equivalent to that of the power method and the number of operation involved is of order (NLK), where K is the number of required iterations.

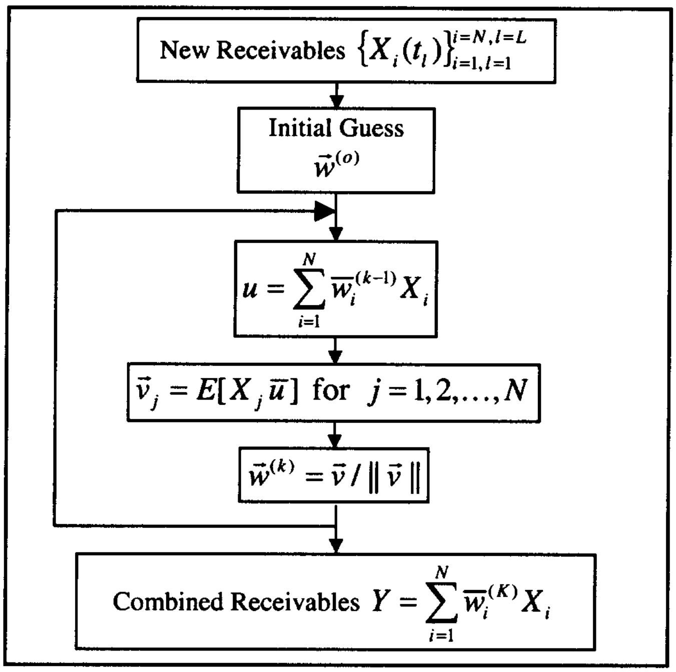

Fig. 4-Proposed Iterative Matrix-free Eigen-based Signal Combining Algorithm

The following relation clarifies the equivalence of the two algorthims given in Figures 3 and 4,

$$\begin{aligned}\vec{v}_j &= E[X_j\vec{u}] \\ &= E[X_j\sum_{i=1}^{N}w_i^{(k-1)}\overline{X}_i] \\ &= \sum_{i=1}^{N}E[X_j\overline{X}_i]w_i^{(k-1)} \\ &= [\Theta_{XX}\vec{w}^{(k-1)}]_j\end{aligned} \quad . \tag{11}$$

The computational saving for the proposed algorithm can be analyzed as follows. Each iteration requires the following operations:

(i) Forming the weighted sum of the receivables

$$u=\sum_{i=1}^{N}\overline{w}_i^{(k-1)}X_i, \tag{12}$$

(ii) Updating the weight by taking the inner product of the weighted sum with each individual receivable

$$\vec{v}_j=E[X_j\vec{u}] \text{ for } j=1,2,\ldots,N, \tag{13}$$

(iii) Normalizing the result gives

$$\vec{w}^{(k)}=\vec{v}/\|\vec{v}\|, \tag{14}$$

The total number of floating point operations needed to find the optimal weight in the proposed algorithm is $(NL+NL+2N)K \sim O(NLK)$, respectively. Note that the number of iterations K is usually much smaller than the array size N and the number of symbols L. In practice, processing the first set of weight from an initial block of symbol may require several iterations. However, when the spacecraft and the ground stations are changing slowly and using the previously found weight as an initial guess, subsequent weights can converge quickly. As will be demonstrated later in the next section, when the geometry of the spacecraft remains unchanged with respect to the array, the next set of weight converges with a small number of iterations; and in most cases only a few iterations are needed.

Our algorithm is unique and remarkable in a sense that the dominant eigenvector is found without the actual formation of the covariance matrices and the number of operations involved is one order less intensive.

Several algorithms have been studied to reduce the computational intensity. Particularly, Choi and Yun [6] casted the maximizing combined output power approach into a Lagrange Multiplier optimization:

$$\max \vec{w}^H\Theta_{XX}\vec{w} \text{ subject to } \vec{w}^H\vec{w}=1. \tag{15}$$

At each time step, Choi and Yun solved the optimization using the modified conjugate gradient method to obtain $\vec{w}$ iteratively and successfully reduce the computational load down to the order (NLK), where K is the number of required iterations. However, like any other high-dimensional optimization schemes, the result often yields a sub-optimal set of weight. Mainly the initial guess may be in the vicinity of a local maximum, which attracts the iterative solutions.

The following table summarizes the flop counts for all the considered algorithms.

Signal Combining Algorithms	**Number of Operations**
Conventional Eigen Method	$O(\max\{N^3,N^2L\})$
Power Method	$O(\max\{N^2K,N^2L\})$
Proposed Matrix-free Method	$O(NLK)$

Table 1–Operation count comparison for various algorithms

We end this section with the following remark. For the case when multiple signal transmitters are present, several primary dominant eigenvectors are needed and each of which will yield a combined signal in accordance to equation (1). The first dominant weight is computed using the proposed algorithms. Subsequent dominant weights are found using the same algorithms, but for the shifted eigen problem and with an extra step of orthogonalizing against the previously found weights. For instance, to compute the second dominant eigenpair $(\lambda_2, \vec{w}_2)$, we repeat our proposed algorithms with Θ_{XX} replaced by $(\Theta_{XX} - \lambda_1)$ and orthogonalize after each or a few iterations using the modified Gram-Schmidt method [10].

3. PERFORMANCE ANALYSIS

Let us analyze the performance of the eigen-based signal combining technique. Suppose the phase vector $[e^{-j\Theta_1}, e^{-j\Theta_2}, \ldots, e^{-j\Theta_N}]$ for the antenna array is known, then in the ideal case, when the receivables are perfectly combined, the weight is the conjugate of the phase vector

$$\vec{w} = \frac{1}{\sqrt{N}}[e^{j\Theta_1}, e^{j\Theta_2}, \ldots, e^{j\Theta_N}]^T, \tag{16}$$

and the combined output signal in (1) becomes

$$Y(t) = \sqrt{N}\,S(t) + \sum_{i=1}^{N} \overline{w}_i n_i. \tag{17}$$

The resulting signal-to-noise ratio for the combined output is

$$SNR_o = \frac{N\,E[|S|^2]}{E[|\sum_{i=1}^{N} \overline{w}_i n_i|^2]} = \frac{N\,E[|S|^2]}{\frac{1}{N}\sum_{i=1}^{N}\sigma_i^2}, \tag{18}$$

where σ_i^2 is the receiver's noise variance. When the receivers' noise variances are the same, the combined output SNR is

$$SNR_o = N\frac{E[|S|^2]}{\sigma^2} = N\,SNR_i. \tag{19}$$

In short, the ideal SNR performance of the eigen-based signal combining approach yields a theoretical gain factor of N over the receiver's input SNR.

4. NUMERICAL RESULTS & DISCUSSIONS

In our simulations, we assume that the arrays are of rectangular configurations and of different sizes. The receivables are constructed based on the following spacecraft and antenna array assumptions. The antennas are separated from another 20 meters in the x-direction and 30 meters in the y-direction. The spacecraft signal arrives in the direction of 30° elevation and 15° azimuth. Ka-band frequency is assumed. The symbols are complex-valued their length within each processing block varies from 5,000 up to 60,000 with increment of 5,000 symbols.

Many combining techniques tend to work well when the input SNR at each receiver is sufficiently large and actually fail when the received SNR is very weak. To demonstrate that our proposed algorithm works even when the SNR is very small, we assume in our simulations that the received SNR at each antenna is $-(7+10\log N)\,dB$ for an array of size N. For example, if $N=128$, the SNR at each receiver is assumed to be $-(28.0721)\,dB$. Both the received input SNR and the theoretical combined output SINR for our considered array configurations are shown in Table 2.

Array Configuration	4×2	4×4	4×8	8×8	8×16
Array Size	8	16	32	64	128
Received Input Symbol SNR	-16.0309 (dB)	-19.0412 (dB)	-22.0515 (dB)	-25.0618 (dB)	-28.0721 (dB)
Theoretical Combined Output SNR	-7.0000 (dB)	-7.0000 (dB)	-7.0000 (dB)	-7.0000 (dB)	-7.0000 (dB)

Table 2 –Array configurations for numerical simulations and the received, combined, and gained symbol SNRs.

Also as suggested in [11], the initial guess for our Power method and the proposed matrix-free algorithms is chosen as,

$$\vec{w}^{(o)} = [1,\ldots,1]^T / \sqrt{N} \tag{20}$$

for faster convergence. Once the optimal weight is found we compute the corresponding SNR, which will be compared with the theoretical combined SNR, -7 (dB). The difference of the two yields the degradation or the combined loss of the symbol SNR.

Numerical simulations are implemented using the direct Eigen algorithm as well as the proposed matrix-free algorithm (Figure 4). The combined symbol SNR losses for different array sizes and symbol lengths are displayed in Figures 5 and 6. Numerical performances, in term of combined output of symbol SNR losses, for both algorithms are exhibited in Table 3.

Array Size	L=30,000		L=40,000		L=50,000		L=60,000	
	EIGEN	PROP	EIGEN	PROP	EIGEN	PROP	EIGEN	PROP
2X4	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
4X4	0.08	0.05	0.07	0.04	0.06	0.03	0.04	0.02
4X8	0.18	0.12	0.14	0.09	0.10	0.06	0.09	0.05
8X8	0.36	0.28	0.27	0.20	0.22	0.16	0.19	0.14
8X16	0.75	0.61	0.57	0.45	0.46	0.35	0.36	0.28

Table 3 – Symbol SNR Loss (dB) Using the Standard EIGEN Method and the Proposed Algorithm.

We found that as the number of symbols per processing block increases the symbol SNR loss diminishes. For instance, in the case when the antenna size is 2X4 and received symbol SNR is –16.0309 (dB) with for L=30,000. In this case, the received symbol SNR losses for the both the Eigen and the proposed algorithms are less than 0.02 (dB).

In addition, one can find from Table 3 that the proposed algorithm produces slightly better results than those of employed by the direct Eigen methods. This is not surprising to us and is simply due to the nature of the involving techniques. Namely, in our proposed algorithm, we form at each iteration the combining sums, for instance, of the receivables (see Figure 4). Such process is beneficial to us in the sense that desired signals are preserved and in fact amplified, while the noise and undesired signals get cancelled. As for the direct Eigen technique, such event does not occur as the covariance matrix is computed instead. Nevertheless all considered algorithms work.

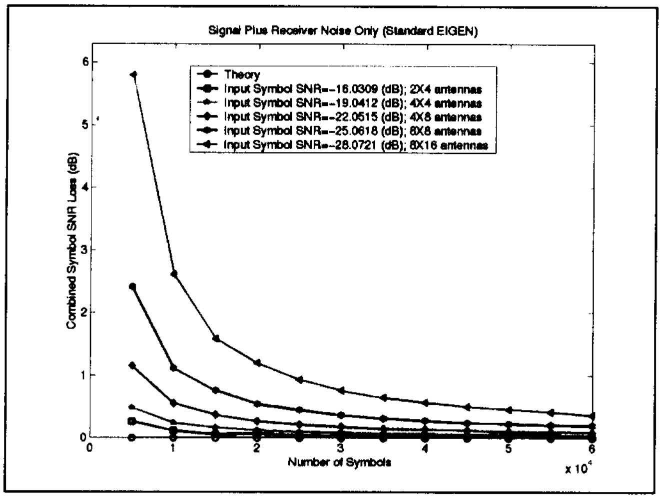

Fig. 5-Symbol SNR loss using the Eigen method.

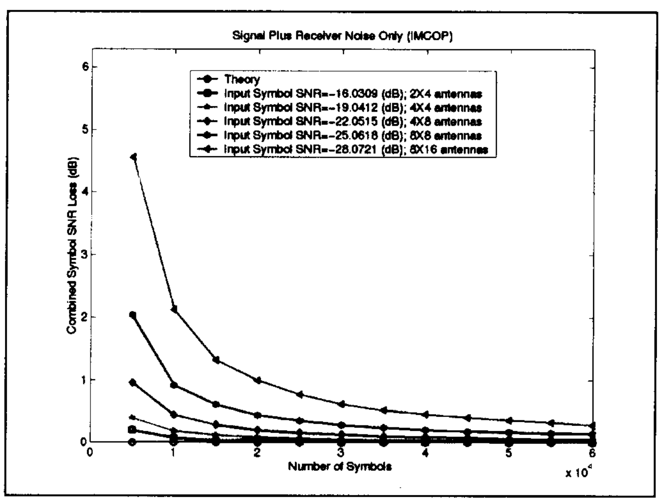

Fig. 6-Symbol SNR loss using the proposed algorithm.

5. CONCLUSIONS

In this paper, we proposed a fast signal combining algorithm, which is based on the Eigen theory and solves iteratively for an optimal weight that maximizes the combined output signal-to-noise ratio. Our proposed scheme is practical in the sense that (i) the resulting optimal weight yields the theoretical combined output SNR, (ii) no covariance matrix is formed during the process and (iii) the proposed algorithm uses the smallest possible amount of computing operations and as well as memory storage; rendering its capability for large-size arrays. Mathematical framework and performance analysis for our algorithm are also presented. Numerical simulations have shown that the proposed algorithm yields excellent SNR performances.

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7. ACKNOWLEDGEMENTS

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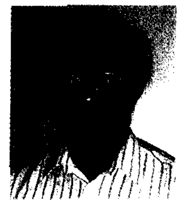

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At M.I.T. he contributed to the development of an experimental over-the-horizon optical communication system operating between Lincoln Laboratory and the M.I.T. campus. During his fellowship at the Hughes Aircraft Company in El Segundo, Calif., he contributed to the development of wideband optical modulators using traveling-wave cavities, and helped develop and demonstrate prototype coherent optical communications systems. He joined the Jet Propulsion Laboratory, Pasadena, Calif., in 1979, where he is a senior engineer in the Digital Signal Processing Research group. He is currently conducting research on various topics in deep-space communications, including real-time electronic compensation for gravity and wind induced deformation of large antennas with focal-plane arrays, adaptive algorithms for optimum combining and tracking of spacecraft with large arrays, improved optical communications through atmospheric turbulence, and the application of quantum communications theory to deep-space communications. He has written or co-authored over 80 articles in refereed journals, conference papers and JPL publications, and has received numerous NASA awards for technical innovations. Dr. Vilnrotter is a member of Eta Kappa Nu, Tau Beta Pi, Sigma Xi, and is a biographee in Marquis Who's Who in Science and Engineering.